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Application and Research of Graph Convolutional Network-based Generative Artificial Intelligence for Redefining Learning and Teaching Paradigms in Digital Education

Xiaoping Tang[1] and Yongmei Ying[1,*]
[1] Yuanpei College, Shaoxing University, Shaoxing, Zhejiang, 312000, China
Corresponding authors: (e-mail: yon_may@sina.com).

Abstract In order to explore the possibility of generative artificial intelligence to help the development of digital educational resources, the value coupling relationship between generative artificial intelligence and the development of digital educational resources is clarified. Issued from the theory of generative artificial intelligence, the generative artificial intelligence technology is designed with the help of generative adversarial graph convolutional network. In order to make the generative AI technology work better in the current digital education, the generative AI embedded in the digital education model is proposed, and the corresponding application effect testing program is developed. Scale testing and SPSS software are used as the main research tools to explore the research program of this paper. After the experimental intervention, compared with traditional digital education, generative AI technology is particularly prominent in improving students' digital literacy, with $P<0.05$ for digital theoretical knowledge ($P=0.003$), digital skills ($P=0.006$), and learning attitudes ($P=0.006$), which fully verifies the prospect of the practical application of generative AI technology in digital education.

Index Terms generative confrontation, graph convolutional networks, generative artificial intelligence, digital education

I. Introduction

Artificial Intelligence (AI), as an emerging technology, is developing rapidly and showing great potential in various fields [1]. Among them, generative AI, as one of the important branches of AI, is not only widely used in the fields of art and literature, but also shows innovative application prospects in the field of education [2], [3]. Generative AI refers to a class of machine learning models based on deep learning, which can generate new, similar but not identical to the original data by learning a large amount of data [4]-[6]. This process of data generation is usually done by giving some initial conditions as inputs and then using deep neural networks and probabilistic models to generate new data step by step [7], [8]. In education, generative AI technology has redefined the learning and teaching paradigm, mainly in personalized teaching, optimization of teaching resources, intelligent tutoring and assessment, etc., which has changed the traditional teaching mode and method [9]-[12].

Generative AI can generate personalized teaching materials based on students' interests, abilities and learning styles [13], [14]. By analyzing students' learning data and feedback, generative AI can customize teaching content and learning paths to fit students' characteristics [15]. This personalized teaching method can improve students' learning effect, stimulate learning interest and reduce learning pressure [16]. In addition, generative AI can provide students with customized learning content based on their learning situation and needs [17], [18]. By analyzing students' learning data, it intelligently recommends textbooks, exercises, and courses that are suitable for students' level to help them better master their knowledge [19], [20]. And with the continuous development of generative AI technology, intelligent tutoring and assessment has been practically applied in many schools and educational institutions as an important application [21]-[23]. Through the use of generative AI technology, students can obtain more personalized tutoring and assessment services, which can improve learning effectiveness and performance [24], [25].

Literature [26] based on the literature review pointed out that the current personalized learning methodology has not been realized as an actionable product, so it constructed a Generative Artificial Intelligence (GAI) tutor for personalized learning and teaching in higher education courses, verified the effectiveness of the system, and continued to evaluate it effectively. Literature [27] analyzed the transformative impact of GAI on personalized STEAM education, examined the integration of AI technologies with STEAM education to provide personalized learning experiences, and emphasized that by leveraging GAI, personalized STEAM education can be extended to a broader audience to promote teaching equity. Literature [28] explores the intersection of GAI and personalization in health professions education (PHE), highlighting that GAI holds great promise for personalizing public health and identifying the need for ethical frameworks and diverse development teams to enable bias and equity issues in the application of AI in education. Literature [29] discusses the use of GAI in education, revealing that it transforms traditional approaches by generating personalized educational materials and providing real-time feedback, and by combining the limitations of traditional education with the potential of future technologies, it suggests that GAI will redefine education to be more personalized, collaborative, and impactful. Literature [30] analyzes and explores curriculum resources and teaching models based on GAI in order to find ways of combining standardization and personalization, showing that through the effective linkage of GAI technology, teachers and students, it is possible to provide assistance for multilevel and personalized teaching and learning in terms of inspiring ideas and case presentations Literature [31] outlines the state-of-the-art large-scale language models developed by technology companies, exploring their different applications and contributions in education, aiming to provide new insights into the enhancement of human-computer interaction in educational environments through the use of GAI, revealing that the current applications of large language models in education are mainly focused on the ChatGPT family. Literature [32] proposed an evaluation index system for AI-generated digital educational resources and constructed a body of indicators for evaluating the quality of AI-generated digital educational resources based on the literature review, and the results showed that the content features are crucial in assessing the quality of AI-generated educational resources, followed by expressive features, and user and technical features. Literature [33] examined the impact of GAI technology on learning performance in the education sector, particularly the mediating roles of e-learning competence (EC), desire to learn (DL), and beliefs about the future (BF), and demonstrated that GAI technology has a significant impact on learning performance by mediating EC, DL, and BF roles. Based on a systematic review, literature [34] describes the perspectives of expert scholars on GAI in education, with the majority of scholars supporting the integration of GAI into education as it provides students with a personalized learning experience and pointing out concerns, proposing a framework for DATS and outlining an optimal path for future GAI applications in schools. Literature [35] examined the use of AI to enhance teaching and learning practices in higher education based on ChatGPT, stating that AI can enhance teaching and learning practices in higher education in a variety of ways, including personalized learning, automated assessment and feedback generation, resource recommendation, time management, etc., and that ethical considerations, such as data privacy and transparency, need to be taken into account when applying AI tools. The above study explores the application of GAI technology in education and acknowledges its impact, which brings innovative learning approaches that help improve learning outcomes such as personalized teaching, optimization and recommendation of teaching resources, and evaluation of teaching and learning, but at the same time, it needs to be aware of the privacy and security issues that it raises.

Based on the theoretical foundation of generative artificial intelligence, a generative artificial intelligence technology based on generative adversarial graph convolutional network is proposed. According to the prospect of the application of generative AI technology in digital education, the design of generative AI embedded in the digital education model is carried out from three aspects, namely, intelligent processing, numerical synergy, and data-driven. Under the implementation of the principle that the results of experimental data are the most powerful evidence to validate the research, a research program on the effect of digital education integrating generative AI technology is formulated, which includes the research object, research idea, research purpose, research object, research tool, and so on. Under the joint action of research data and tools, the research program of this paper is validated and analyzed.

II. Generative Artificial Intelligence Based on Graph Convolutional Networks

II. A. Generative Artificial Intelligence

II. A. 1) Theoretical Foundations of Generative Artificial Intelligence

Generative AI refers to methods and models that utilize machine learning techniques to generate new data with some specific properties. Among them, VAE, GAN, FLOW, and Diffusion are representative algorithms in generative AI.VAE is a neural network-based generative model whose goal is to learn the latent distribution of the data and generate new data by random sampling. The main core idea of VAE is to use a self-encoder to encode the input data and sample the encoded deep space to get new data. Unlike traditional autocoders, VAE introduces latent variables during the encoding process and trains the model by maximizing the log-likelihood of the generated data. Due to the introduction of latent variables, VAE is able to learn the distribution of the data and generate new data that conforms to the distribution. GAN is a generative model based on adversarial learning, whose goal is to learn the distribution of the data and generate new data that conforms to the distribution. GAN consists of a generator, whose goal is to generate data as realistic as possible, and a discriminator, whose goal is to differentiate between the data generated by the generator and the real data. GAN optimizes the model by alternately training the generator and the discriminator and generates realistic new data. FLOW is a generative model based on reversible neural networks, whose goal is to learn the latent distribution of the data and generate new data by transforming the latent space. The main idea of FLOW is to map the input data into the latent space by a reversible neural network and optimize the network parameters by using gradient backpropagation algorithm to optimize the network parameters so that the distribution obtained after mapping is closer to the standard normal distribution.

II. A. 2) Generative Artificial Intelligence Enabling Education

Generative AI relies on deep learning and machine learning models to provide technical support for educational scenarios. Its core technologies include Generative Adversarial Network (GAN), Variational Autocoder (VAE) and Diffusion Model, which empower the personalized and diversified development of education through dynamic content generation, virtual scene creation and multimodal optimization. These technologies are not only of theoretical significance, but their value lies in the ability to combine with educational scenarios to effectively solve complex problems in the education system. For example, in virtual laboratory teaching, VAE technology generates a virtual chemistry laboratory assistant, which allows students to complete complex experimental operations through interaction, reducing the cost and risk of experiments, while improving practical skills. In the “Smart Classroom” project, generative AI technology monitors students' knowledge mastery in real time, recommends higher difficulty tasks for high performers, and provides additional video explanations for those who encounter difficulties, which significantly improves learning efficiency. In art education, GAN's style migration technology can convert students' sketches into Impressionist or Cubist styles, helping students understand the characteristics of different art genres and stimulating creativity.

II. B. Generative Artificial Intelligence Design

II. B. 1) Graph Convolutional Neural Networks

Graph Convolutional Neural Network (GCN) is a neural network model for processing graph-structured data [36]. Compared to traditional convolutional neural networks, GCN can process non-Euclidean-structured data, such as social networks and multimedia teaching data. Graph Convolutional Neural Network is a deep learning model that can handle graph-structured data, and its basic idea is to generalize the convolution operation to graph-structured data [37]. By defining a convolution operation based on graph structure, GCN can realize the effective extraction and representation of node features, so as to realize the classification, regression and other tasks of graph-structured data.

(1) Graph structure representation

The graph data with its adjacency matrix is shown in Figure 1.The graph structure data consists of nodes and edges. Nodes represent entities of the data, which can be people, objects, events, etc. Edges represent relationships between entities, which can be connections, similarities, etc. In GCN, the graph structure is usually represented by an adjacency matrix, and the adjacency matrix A is a matrix of $N \times N$, where N is the number of nodes, and A_i denotes whether or not there is an edge between node i and node j, and if there is an edge, the value of A_{ij} is 1. Otherwise, the value of A_{ij} is 0. The 6×6 matrix on the right side of the graph is the adjacency matrix of the graph structure data consisting of the six nodes on the left side of the graph. Since node 1 and node 2 are connected to each other, the value of the second column of the first row of the adjacency matrix is 1, and the value of the first column of the second row of the adjacency matrix is likewise 1. Node 4 and node 5 are not connected to each other, so the value of the fourth column of the fourth row as well as the value of the fourth column of the fifth row of the adjacency matrix is 0. In addition to this, the value of A_{ij} can also be used. Adjacency matrix, a degree matrix can also be used to represent the graph structure. The degree matrix D is a matrix of $N \times N$, where D_i denotes the degree of node i, i.e., the number of edges connecting node i to other nodes. The diagonal elements of the degree matrix can be obtained by summing the adjacency matrices, i.e.:

$$D_{ii} = \sum_{j=1}^{N} A_{ij} \tag{1}$$

In GCN, in addition to nodes and edges, each node needs to be endowed with an initial feature vector, denoted by $X \in R^{N\times d}$, where d denotes the dimension of the feature vector and N denotes the number of nodes. The feature vector of a node can represent the attributes of the node or other relevant information, and in the human skeleton behavior recognition dataset, the general feature of a node is represented as the position information of the skeletal node.

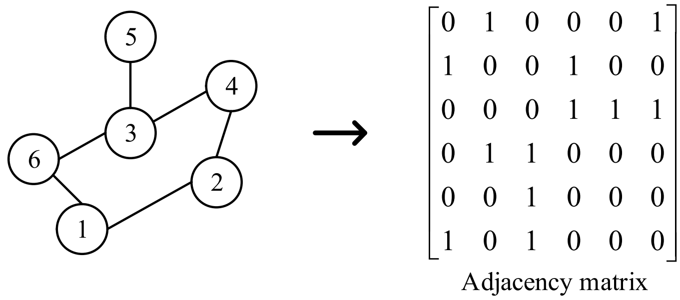


Figure 1: Graph data and its adjacency matrix

(2) Graph Convolution Operations

In Euclidean space, the convolution operation is usually implemented by means of a filter and a pooling operation. A filter is a set of learnable weight matrices used to extract features from the input signal. The pooling operation, on the other hand, is used to downsample the input signal, thus reducing the number of parameters and computational complexity. In graph-structured data, on the other hand, the traditional convolution and pooling operations cannot be directly applied because the number, types, and connections of nodes and edges may change. In order to solve this problem, a graph convolution operation based on the adjacency matrix and node features is proposed, where the values of the adjacency matrix correspond to the connection relations of the row and column nodes. The graph convolution operation can be expressed by the following equation:

$$H^{(l+1)} = \sigma(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}) \tag{2}$$

where $H^{(l)} \in R^{N\times d}$ denotes the node identity matrix of the l th layer, $W^{(l)} \in R^{d^{(l-1)}\times d^{(l)}}$ denotes the weight matrix of the l th layer, and $A = A + I$ denotes the adjacency matrix The result after adding the self-loop, D is the diagonal element of the degree matrix A. The $\sigma(\cdot)$ is the activation function, commonly used functions such as Relu and Sigmoid.

In Eq. (2), the part of $AD^{\frac{1}{2}}AD^{-\frac{1}{2}\frac{1}{2}}$ can be interpreted as a weighted average of the adjacencies between nodes. Specifically, $D^{\frac{1}{2}}AD^{-\frac{1}{2}}$ weights the connections between nodes i and j with a weight of $\frac{1}{\sqrt{D_{ii}D_{ij}}}$. This has the advantage of aggregating the features of connected nodes to obtain a more comprehensive node representation. In addition, to ensure that the dimensionality of the node features remains constant, the GCN uses a weight matrix $W^{(l)}$ to linearly transform the feature vectors. This weight matrix is learnable and can be updated by back propagation algorithm. With the above formulation, GCN implements a convolution operation on graph-structured data, which is able to aggregate and learn the relationships between nodes, resulting in a more robust and efficient node representation.

GCN can stack multiple convolutional layers to get more complex and deeper models. In each layer, GCN can aggregate and learn the node features to get a more comprehensive and advanced node representation. With multi-layer GCN models, multiple iterations and learning of node features can be performed to obtain more comprehensive and advanced node representations. These node representations can be used for tasks such as node classification, node clustering, and graph classification.

(3) Applications of GCN

GCN has a wide range of applications in the processing and analysis of graph-structured data, such as node classification, graph classification, and graph generation. Several typical application scenarios are described below.

a) Node Classification

Node classification refers to classifying nodes in a graph structure into different categories.GCN can learn the relationships and features between nodes to obtain more robust and effective node representations, which can be used for node classification tasks.

b) Graph classification

Graph classification refers to classifying the whole graph structure into different categories.GCN can aggregate and learn the whole graph by learning the relationships and features between all the nodes so as to get more robust and effective graph representations which can be used in graph classification tasks. The graph classification task has a wide range of applications in areas such as teacher-student interaction and teaching resource recommendation systems.

c) Graph Generation

Graph generation refers to generating new graph structures based on given features and rules.GCN can realize the graph generation task by learning the relationships and features between nodes and generating new graph structures. Specifically, the goal of the graph generation task is to generate new graph structures based on given features and rules. The graph generation task has a wide range of applications in the fields of multimedia teaching, immersion teaching, and personalized teaching.

II. B. 2) User's potential friends

In this paper, a randomized wandering approach is used at each user node to obtain n user sequences of a specific length, where the randomized wandering approach is subject to three constraints. On the one hand, a buddy with high connection strength is selected as the user's next node. On the other hand, a dominant buddy is selected as the user's next node. On the other hand, the buddy node which has not been wandered is selected as the next node of the user.Finally, the user sequence is input into Skip-Gram to obtain the potential characteristics of the user, and the cosine similarity is used to obtain the top-k buddies of the user, for which the potential buddies of the user are established.

II. B. 3) Feature extraction

In this paper, we will use graph convolutional neural network to obtain the structural features of the rating information, recursively to obtain the potential features of the user and the product in multiple propagation layers, and use the weighted sum to obtain the final potential representation to achieve the personalized recommendation of the user, which is represented as follows:

$$p_i^{(k+1)} = \sum_{j \in N_i} \frac{1}{\sqrt{|N_i| \times |N_j|}} q_j^{(k)} \tag{3}$$

$$q_j^{(k+1)} = \sum_{i \in N_j} \frac{1}{\sqrt{|N_i| \times |N_j|}} p_i^{(k)} \tag{4}$$

Here, $p_i^{(k)}$ and $p_i^{(k+1)}$ are the potential features acquired by the user at k and $k+1$ levels, respectively. $q_j^{(k)}$ and $q_j^{(k+1)}$ are the potential features acquired by the product at k and $k+1$ layers, respectively. N_i and N_j are users i who have liked the product, clicked on or purchased the product j.

For each user, the update of its feature embedding can be realized not only by the purchased products, but also by the embedding of the user's potential friends, which is represented as follows:

$$p_i^{(k+1)} = \sum_{jeN_i} \frac{1}{\sqrt{|N_i| \times |N_j|}} q_j^{(k)} + Pool(p_z^{(k)}) \tag{5}$$

Here, $p_z^{(k)}$ is the potential features acquired by the user's potential buddy z at the k level. The $Pool(\cdot)$ function can be an averaging function that averages the potential embeddings of the trusted buddies to realize the information dissemination of the trusted buddies. The features of the end user and the product are represented as:

$$p_i = \frac{1}{L}(p_i^{(0)} + p_i^{(1)} + \cdots + p_i^{(L)}) \tag{6}$$

$$q_j = \frac{1}{L}(q_j^{(0)} + q_j^{(1)} + \cdots + q_j^{(L)}) \tag{7}$$

Here, L is the number of propagation layers, multi-layer propagation can be realized by recursive way, in order to realize the Top-N recommendation of the product, this paper adopts BPR function as the loss function, which is expressed as follows:

$$\Omega_{BPR} = \sum_{(i,j,k)eo} -\log \sigma(x_{ij} - x_{ik}) + \lambda \| \phi \| \tag{8}$$

$$x_{ij} = p_i^T q_j \tag{9}$$

where k is a product that the user has not yet purchased, then the user's preference for the purchased product j is better than the preference for the product k that has not yet been purchased. λ is the regularization coefficient. Φ denotes the model parameters. o is a set of user i 's favorites for purchased product j and user i 's favorites for unpurchased product k .

II. B. 4) Mathematical modeling

In generative adversarial graph convolutional network, the generative model G is responsible for filtering credible friends for the user, and at the same time, the friend loves the products that the user has purchased and has similar preferences with the user, and in the discriminative model D , the loss function is as follows:

$$\Omega_{GAN} = \min_{D_\phi} \max_{G_\theta} -\log \sigma(x_{ij} - x_{zj}) \tag{10}$$

Here, x_{ij} denotes the degree of favoritism of the user for the viewed products. x_{zj} denotes the degree of favoritism of friend z over the user's favorite products. p_i and q_j are the latent features of user i and product j , respectively, obtained by graph convolutional neural network, which are deep features containing rich information. Its computational formula is as follows:

$$P_i(v \mid S_i) = \frac{e^{v|S_i}}{\sum e^{v'|S_i}} \tag{11}$$

Here, S_i is the potential buddy of user i . v is the reconstructed buddy. The specific calculations are as follows:

$$\hat{v} = \mathrm{softmax}((\log(P_i) + G_k) / \lambda_1) \tag{12}$$

$$G_k = -\log(-\log(\varepsilon_k)) \tag{13}$$

Here, λ_1 is a parameter greater than 0. The smaller the value, the closer it approximates the true discrete distribution. G_k is the noise. ε_k follows a uniform distribution. $\hat{v}$ is the credible buddies obtained from sampling.

In the generative model of this paper, the ratings of the user's friends on the products that the user has loved will be close to the user's ratings on that product, and the parameters are optimized as follows:

$$\theta = \arg\max_{\theta} -\log \sigma(x_{ij} - x_{zj}) \tag{14}$$

In the discriminative model, users give higher ratings to their favorite products relative to their friends, and the parameters are optimized as follows:

$$\phi = \arg\min_{\phi} -\log \sigma(x_{ij} - x_{zj}) \tag{15}$$

In this paper, we will couple the BPR model and generative adversarial training to realize the prediction of user preference, and the final loss function is represented as follows:

$$\Omega = \Omega_{BPR} + \gamma \Omega_{GAN} \tag{16}$$

Here, γ is the coefficient that controls the optimization of the generative adversarial network.

III. Applications of generative artificial intelligence in digital education

III. A. Opportunities for the use of generative AI in digital education

III. A. 1) Promoting the goal of digital literacy for all

“The digital adaptability, competence and creativity of the whole population will be significantly improved” is the overall requirement and development goal of the Outline based on the current status of the development of digital literacy and skills of the whole population, and the new generation of artificial intelligence represented by generative adversarial graphic convolutional networks provides new opportunities for realizing the goal of improving the digital literacy of the whole population.

(1) The introduction of Generative Adversarial Convolutional Networks has changed the paradigm of citizens' learning, introduced a new digital concept mainly based on artificial intelligence for citizens, and explained the

relevant concepts and simulated the relevant scenarios through the generation of content, so as to improve the acceptance of the new digital concepts by citizens. Generative Adversarial Graph Convolutional Networks on the one hand has an impact on the existing work, forcing citizens to master a higher level of thinking ability, and on the other hand can analyze the current development of digital society to give advice on the cultivation of digital thinking, and make relevant guidance.

(2) Generative Adversarial Convolutional Networks provide citizens with convenient access to knowledge. Generative Adversarial Convolutional Networks can analyze the skills and knowledge needs of jobs according to the input content and give the skills and knowledge needed for the future development of jobs based on the relevant data, so that citizens can improve their relevant abilities according to the current needs and future needs. Not only can it provide personalized services based on the input tasks, but it can also answer questions and provide relevant knowledge and information in various fields.

III. A. 2) Promoting a diversified shift in learning styles

Digital literacy education for all is a huge project that requires the joint participation of multiple subjects. With the continuous development of artificial intelligence, generative AI represented by generative adversarial graph convolutional network provides convenient conditions for the diversified transformation of digital literacy learning mode by creating new subjects and uniting the original subjects, which helps to form a digital literacy education system of human-computer interaction and multi-party union. Generative Adversarial Graph Convolutional Network provides convenient conditions for different subjects to jointly participate in digital literacy education. At present, the government, libraries, educational institutions, enterprises and other subjects through the formulation of policies, provide resources, classrooms and other ways to help the people's digital literacy and skills enhancement, but due to the different subjects of the resource construction, funding, personnel composition and other aspects of the existence of large differences, some subjects do not have to carry out the ability to carry out the conditions of digital literacy education, in this case, the generation of the adversarial graph convolution network provides an inexpensive and convenient way for the people to participate in digital literacy education. In this case, the generative adversarial graph convolutional network provides a low-priced and convenient channel, only through the support platform can use the generative adversarial graph convolutional network to obtain the relevant digital literacy education resources, to promote the smooth progress of related teaching.

III. A. 3) Enriching the pedagogical paradigm of digital education

Digital education has been improving with the continuous development of digital technology, and the teaching paradigm has evolved from offline face-to-face teaching to today's online documents, audio and video combinations, live broadcasts, webinars, games, and other methods. The combination of digital literacy education and artificial intelligence technology is a general direction at present, and is also a clear requirement of the Outline, and generative AI represented by generative Adversarial Graph Convolutional Networks provides a new teaching paradigm for digital literacy education. Adversarial graph convolutional networks enable a dialogue-oriented personalized digital education paradigm. Through adversarial graph convolutional networks, users can access a large number of digital literacy education resources, access tools and specific knowledge by inputting simple requirements, and through a sequential task execution system, users can also ask continuous questions on specific issues to meet the learning needs of specific topics.

III. B. Generative AI embedded in digital education models

III. B. 1) Intelligent processing of digital educational resources

Digital education is a lifelong cultivation for the general public, which not only requires huge human and material resources for construction, as well as maintaining a regularized training mechanism for the whole population, but also faces the major problem of being difficult to keep up with the iterative speed of digital technology and its wide-area applications for a long time. Generative AI models represented by generative adversarial graphical convolutional networks are sequentially embedded in the field of digital literacy education, automatically generating a quantifiable digital literacy knowledge annotation system by pooling and using training data with complex sources, timely access, and rich content, and then building an interactive and personalized digital literacy teaching resources recommendation framework to optimize the use of instructor resources and teaching tools in digital literacy education, which to a certain extent alleviates the problem of digital literacy education. To a certain extent, it alleviates the reality of the serious shortage of teaching subjects in digital literacy education, avoids subjectivity and arbitrariness in assessment under the shortage of teaching resources, and gradually forms digital literacy teaching resources with intelligent processing.

III. B. 2) Digital Literacy Teaching and Learning Processes for Digital Intelligence Synergy

Building generative artificial intelligence plug-ins based on generative adversarial graph convolutional networks, intelligent real-time data retrieval, knowledge base information transfer or execution of various operations on behalf of the user, automatic generation of digital literacy teaching process design, arrangement of teaching tools as well as personalized question and answer and test question rubrics, and continuous improvement of the content of digital literacy thematic education, general education, teaching training, project practice and teaching games, The pace and difficulty of digital literacy thematic education, general education, pedagogical training, project practice and pedagogical games are continuously improved, fully respecting the right of choice of the recipients, guiding them to construct learning paths according to a reasonable pace through technological means, cultivating their independent learning and problem-solving abilities and awareness, and ensuring that the recipients are able to receive targeted guidance on digital literacy instruction on a continuous basis.

III. B. 3) Data-driven feedback on digital literacy instruction

Traditional digital literacy teaching assessment systems use feedback testing mechanisms with fixed difficulty coefficients, making it difficult to effectively reveal the individual abilities, willingness to participate, and learning styles of instructors. Artificial intelligence technology, represented by generative adversarial graph convolutional network, embedded in digital literacy teaching feedback, can efficiently process massive correlated data, and then reveal the personal habits of different instructors in digital literacy teaching, the nuances of the teaching content, and the differentiation of the teaching experience, so as to construct a fairer evaluation standard of the effectiveness of the teaching and the content of the feedback mechanism. Rapidly mining the performance data, preference data, demand data and ability data of the instructors, and extracting specific skill annotations, knowledge point annotations and learning style annotations from the relevant massive question bank data according to the abnormal behaviors and potential problems reflected in the personalized analysis of digital literacy learning, so as to update the content of the feedback of digital literacy teaching and to overcome the traditional training data which is too outdated, complicated and erroneous, and complicated and incompatible with the data analysis and feedback mechanism of digital literacy teaching. It overcomes the defects of traditional training data being too old, logical calculation being complicated and wrong, data analysis and visualization being insufficient, qualitative and quantitative mathematical problems being difficult to deal with, and dialogue interaction being too single, etc., and becomes an important support for data-driven digital literacy teaching feedback.

IV. Research design for practical application effects

IV. A. Purpose and target audience of the study

IV. A. 1) Purpose of the study

The purpose of this study is to apply the generative AI technology based on generative adversarial graph convolutional networks to actual digital literacy teaching practices, and to verify through practice whether the technology is applied to real classrooms and is beneficial to the development of users' digital literacy.

IV. A. 2) Objects of study

The practical object of this study is the first-year students of a university, selected as the experimental group class with a total of 20 students and the control group class with a total of 20 students. The reasons for selecting the first-year students of a university as the subjects of this study are as follows: firstly, since the students have already received digital education for two years, they have a basic understanding of the operation of computers and have been familiarized with the basic contents of digital education. Second, the freshmen students were able to understand the structure of the relevant scales and the meaning of the questions, which could ensure the validity of the assessment data.

IV. B. Teaching and learning environment and design thinking

IV. B. 1) Teaching and learning environment

The practice school chosen for this study is a key university, and the computer room in which the teaching practice is carried out has one teacher machine and 60 student machines, and is equipped with facilities and equipment such as sound, interactive whiteboard, etc. The version of scratch 3.0 is installed on each computer, and all computers are connected to the network. The teaching mode of the experimental group was based on generating adversarial graph convolutional networks, while the teaching mode of the control group was the traditional teaching mode. To ensure the rigor and practicability of the research design, all were taught by the same instructor, and the classroom environments were kept the same.

IV. B. 2) Design Ideas

The teaching practice of this study is divided into three phases: teaching preparation, teaching implementation, and effect analysis. The details are as follows:

Teaching preparation stage: study the standards and textbooks, carry out the analysis of the learning situation and interpretation of the textbooks, analyze the teaching objectives and contents, choose appropriate contents, and design teaching cases.

Teaching implementation stage: before carrying out teaching, students are given a pre-test of digital literacy, and the results of the pre-test are taken as the level of students' digital literacy before teaching. Then three rounds of teaching practice were carried out, the main contents include: digital theoretical knowledge, digital skills and learning attitudes, etc., and 2 class hours were arranged every week, totaling 8 class hours.

Effect analysis phase: conduct digital literacy post-tests and interviews with students, interviews with listening teachers, summarize students' digital literacy test data after each round of teaching practice, analyze the content of the pre and post-tests and the interview results, and verify whether generative AI based on Generative Adversarial Graph Convolutional Networks is effective for the development of students' digital literacy.

IV. C. Research tools

IV. C. 1) Test scales

On the basis of previous research results, the students' digital literacy test scale was designed from the three dimensions of digital theoretical knowledge, digital skills and learning attitudes, and each dimension of the scale contains five question items, totaling 15 question items. There are five choices on each item, which are satisfactory, more satisfactory, basic satisfactory, less satisfactory, and unsatisfactory, corresponding to the quantitative values of 5, 4, 3, 2, and 1. After completing the work of designing the students' digital literacy test scale, the distribution of the measurement form was begun as a way of obtaining the data for this study.

IV. C. 2) SPSS data analysis software

SPSS name for statistical products and services solutions. SPSS has always been its distinctive features in the statistical software, and SAS (another statistical analysis software) is known as today's most authoritative two major statistical software. SPSS has a powerful statistical analysis and data preparation functions, convenient charting functions, as well as broad compatibility, interface friendliness to meet the needs of the majority of users, by the majority of the application of statistical analysis of the staff's favorite. SPSS's basic functions include data management, statistical analysis, graphical analysis, output management, etc. The SPSS statistical analysis process, including descriptive statistics, comparison of means, the general linear model, correlation analysis, regression analysis, log-linear model, cluster analysis, data simplification, survival analysis, time series analysis, multiple response and other categories, each category is divided into a number of statistical processes, such as regression analysis is divided into linear regression analysis, curve estimation, Logistic regression, Probit regression, weighted estimation, two-stage least squares, nonlinear regression, and other statistical processes, and each process allows for multiple statistical processes. SPSS also has a specialized plotting system that allows users to draw various graphs based on the data.

V. Generative AI model validation and application analysis

V. A. Generative AI Model Validation Analysis

Experiment is a powerful evidence to test the model, and the validity of the proposed model is verified by experiment and analyzing the experimental results. Firstly, the configuration of the experimental requirements is given, then the experiment-related preparations, such as datasets, performance indexes and comparison experiments, are introduced, and finally the related experimental results are analyzed in detail.

V. A. 1) Experimental environment configuration

Before starting the experimental analysis, the experimental environment is set up with Intel Core i7-6850K CPU, NVIDIA Titan Xp GPU, 32G RAM, Windows 11 (32-bit) OS, Python version 4.5, Cuda version 8.5.3, and TensorFlow version 1.17.

V. A. 2) Preparation of the experiment

(1) Datasets

Experiments were conducted on three publicly available datasets from the real world, datasets A, B, and C. All three datasets provided explicit ratings of items by users, and the explicit ratings of the datasets were converted to the number 1 in the experiments to obtain implicit feedback data indicating that there was an interaction between the user and the item. In order to ensure the quality of the datasets and to facilitate the alignment of the number of interactions of different users, the datasets were preprocessed before conducting the formal experiments, retaining users with at least 10 interactions and at most 100 interactions, and the statistical information of the three datasets after preprocessing is shown in Fig. 2. It can be clearly seen that all values of dataset C are larger than those of datasets A and B. For each dataset, we use the first 80% of items from each user's historical interaction data as the training set, and the remaining 20% of items as the testing set. Based on this division strategy, the model can generate a Top-N list to evaluate the model.

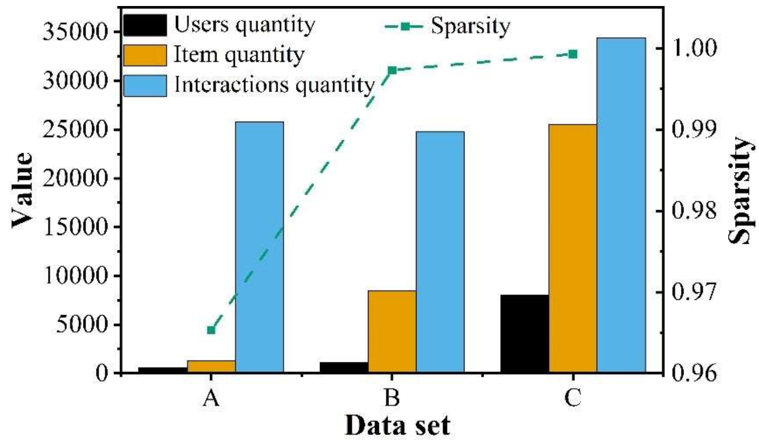


Figure 2: Statistics for three data sets

(2) Performance metrics

Precision rate, recall rate and normalized discount cumulative gain (NDCG) in Top-N recommendation are used as performance metrics, with N taken as 5 and 10.

Precision rate, also known as checking accuracy rate, is used to indicate the ratio of the number of real user interaction items in recommended items to the total number of recommended items. I.e:

$$precision = \frac{\sum_u \left[R(u) \cap T(u) \right]}{\sum_u \left[R(u) \right]} \tag{17}$$

Where, $T(u)$ is the set of items that users u interacted with in the test set of items to be recommended, and $R(u)$ is the set of recommended items.

Recall (Recall): also known as the check all rate, is used to represent the ratio of the number of real user-interacted items in the recommended items to the number of user-interacted items in the test set. I.e:

$$recall = \frac{\sum_u \left| R(u) \cap T(u) \right|}{\sum_u \left| T(u) \right|} \tag{18}$$

Normalized Discounted Cumulative Gain (NDCG), an evaluation metric used to represent the quality of recommendation list ranking. To wit:

$$CG_N = \sum_{i=1}^{N} r_i \tag{19}$$

$$DCG_p = \sum_{i=1}^{p} \frac{2^{r_i} - 1}{\log_2(i+1)} \tag{20}$$

$$IDCG_p = \sum_{i=1}^{|REL|} \frac{2^{r_i} - 1}{\log_2(i+1)} \tag{21}$$

$$NDCG_p = \frac{DCG_p}{IDCG_p} \tag{22}$$

(3) Comparison of algorithms

The proposed GCNGAN is compared with the following algorithms:

a) MostPop: This algorithm recommends to the user the item with the highest popularity, i.e., the item with the highest number of interactions, from the currently available items.

b) BPR-MF: This algorithm optimizes the standard matrix decomposition model by using a pair-by-pair BPR loss function.

c) IRGAN: This algorithm is the first to apply GANs to recommender systems, where the generative model tries to generate and filter an index of items relevant to a given user, and the discriminative model tries to distinguish between user-interacted items from the real world and items generated by the generative model.

d) CFGAN: This algorithm is also a recommendation algorithm based on GANs, and its generative model attempts to generate a vector of user purchases consisting of real-valued elements, rather than sampling an index of individual items that may be of interest to the user.

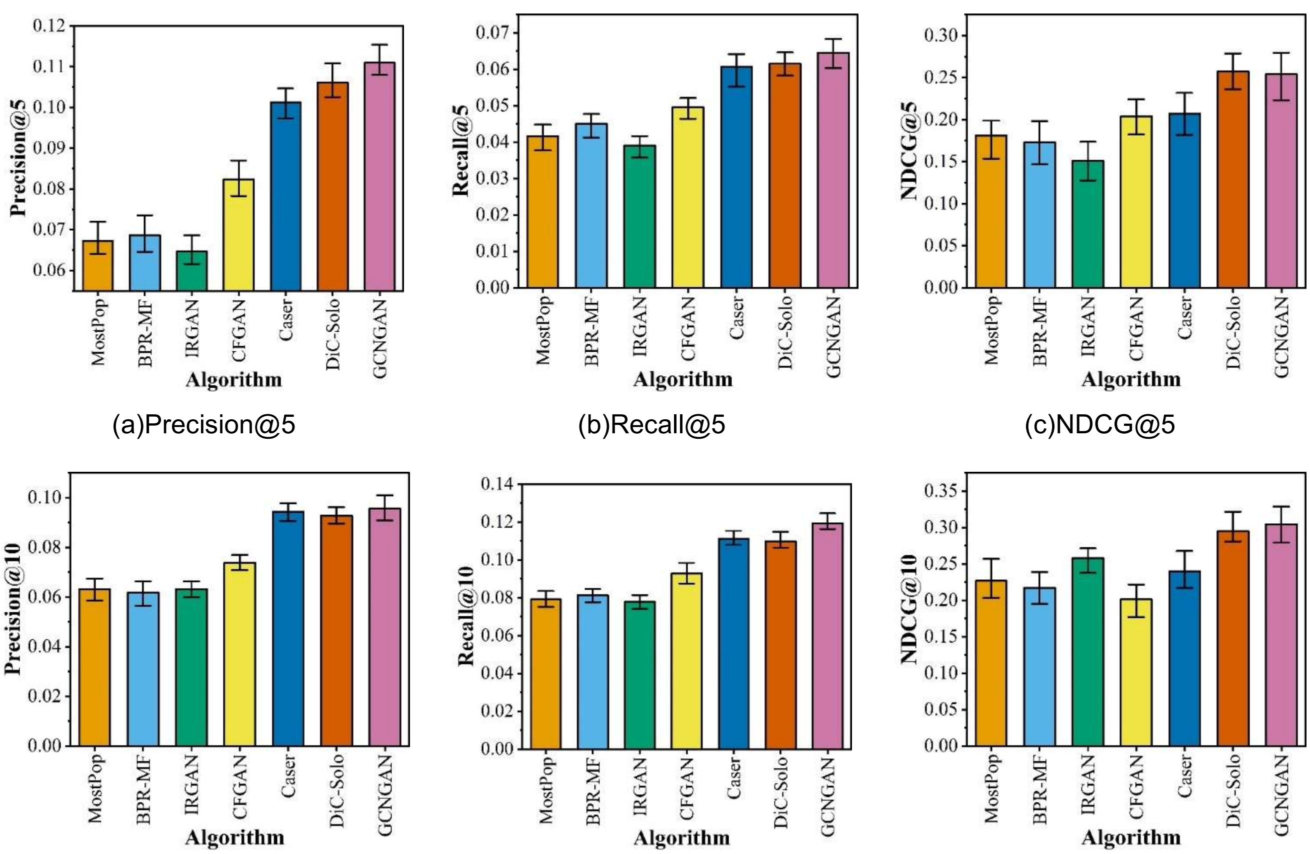
e) Caser: this algorithm is the first method to learn user sequential patterns and thus sequential recommendation using convolutional filters. For a fair comparison, we modify the input of Caser to be the same as the method proposed in this paper, i.e., all items interacted by the user.

f) DiC-Solo: This algorithm represents a variant of the DiCGAN method that uses only generative models and is trained with a point-by-point objective function.

V. A. 3) Analysis of experimental results

(1) Comparative experimental performance analysis

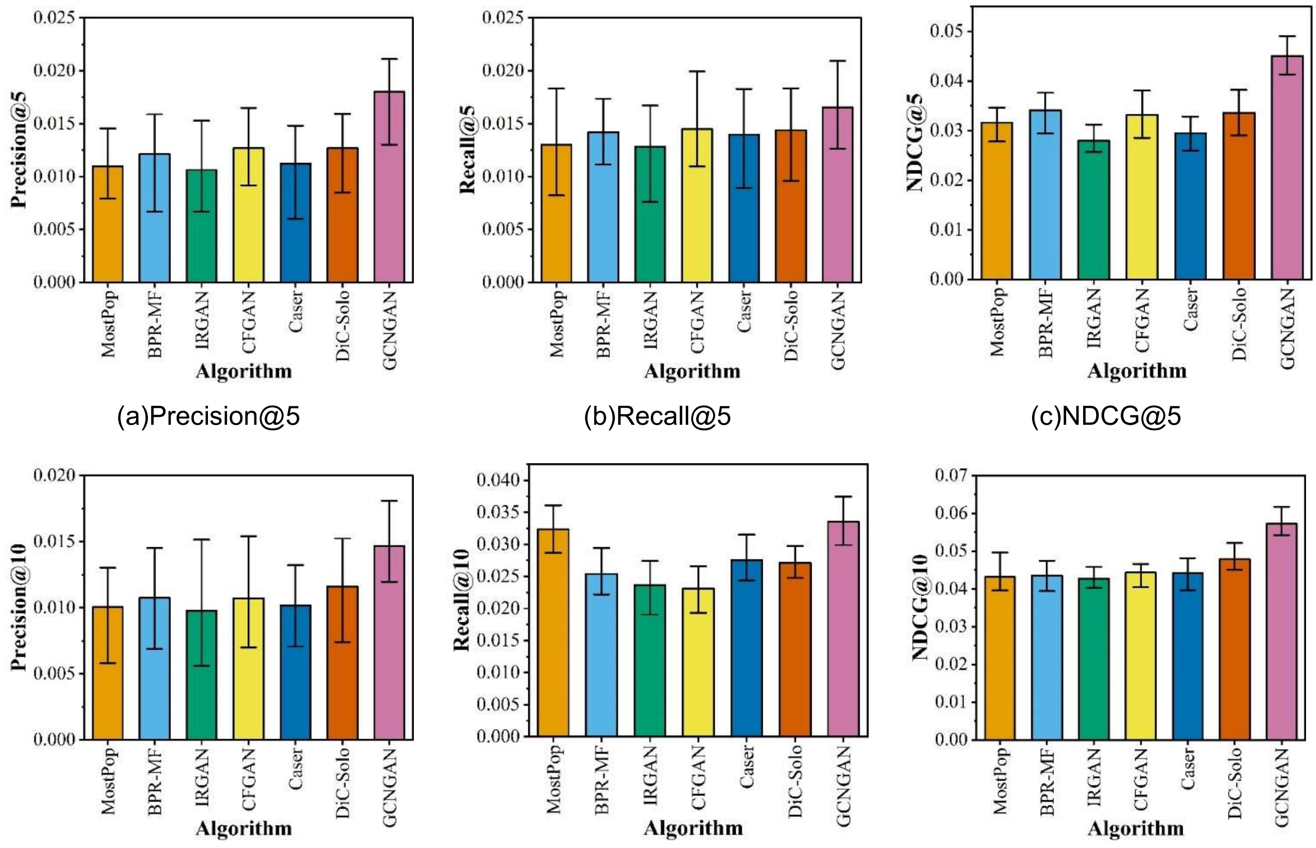
In order to compare the performance of the GCNGAN algorithm proposed in this paper and the comparison algorithm and verify the effectiveness of GCNGAN, the performance comparison of datasets A, B, and C is shown in Fig. 3~Fig. 5, where (a)~(f) are Precision@5, Recall@5, NDCG@5, Precision@10, Recall@10, and NDCG@10, respectively. For dataset A, GCNGAN is about 9.46% higher than the best performance in the comparison algorithm Precision@5, 5.49% on Recall@5, 14.26% on NDCG@5, 0.296% on Precision@10, 0.023% on Recall@10, and 7.57% on NDCG@10. The same is true for other datasets B and C, which will not be described in detail.



(a)Precision@5 (b)Recall@5 (c)NDCG@5

(d)Precision@10 (e)Recall@10 (f)NDCG@10

Figure 3: Algorithm performance comparison on dataset A

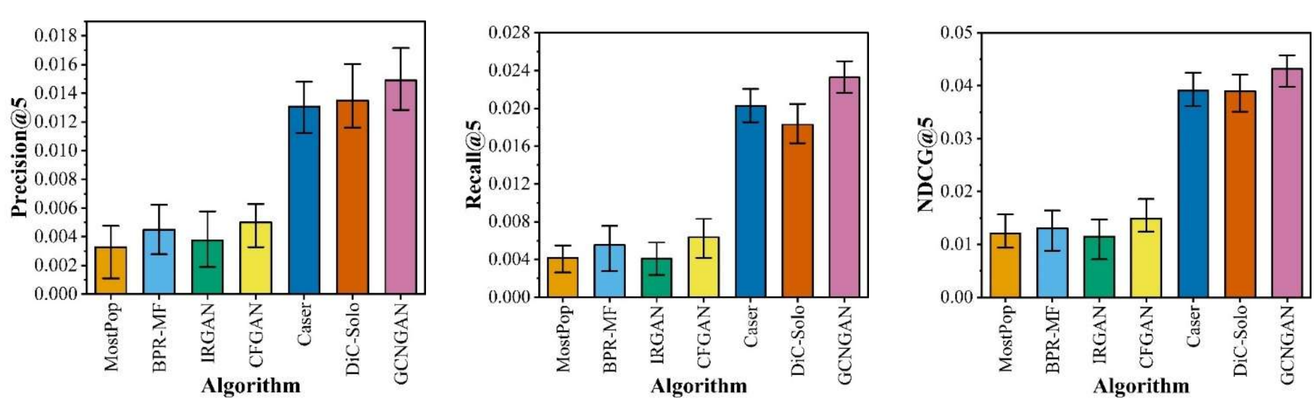


(a)Precision@5 (b)Recall@5 (c)NDCG@5

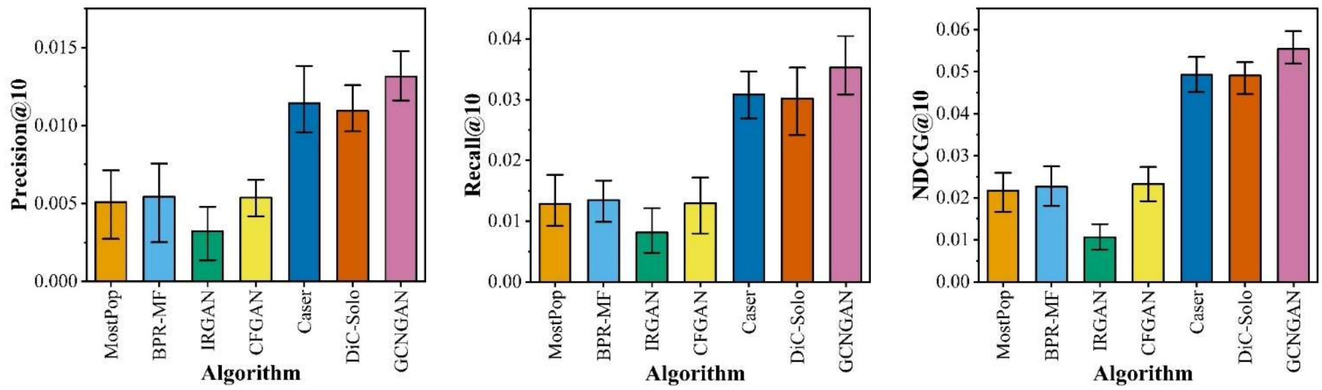
(d)Precision@10 (e)Recall@10 (f)NDCG@10

Figure 4: Algorithm performance comparison on dataset B

In order to further compare the performance among the recommendation algorithms based on generative adversarial networks in detail, Fig. 6 gives the growth trend of Precision@10 during the training process of three GAN-based recommendation algorithms, IRGAN, CFGAN, and GCNCGAN, on datasets A and B, where (a)~(b) are dataset A and dataset B. The experiment sets up an early-stopping mechanism, so that the training will be stopped if the Precision@10 does not increase for 50 consecutive training steps, the training will stop.The performance of IRGAN is the worst on both Movie and Ciao datasets. This is mainly due to the fact that the way IRGAN generates data label indexes faces the problem of chaotic data labels and cannot take full advantage of discriminative models, whereas CFGAN and GCNGAN overcome the limitation of IRGAN by using vector-level adversarial training.GCNGAN uses only vectors of interacting items to perform convolutional operations, which is less sensitive to the sparsity of the data, and thus allows for faster better learning.

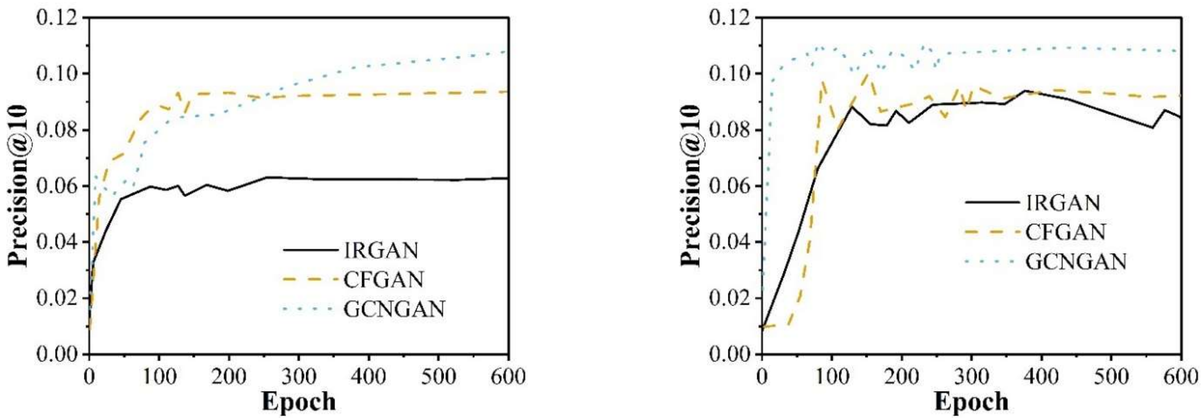


(a)Precision@5 (b)Recall@5 (c)NDCG@5



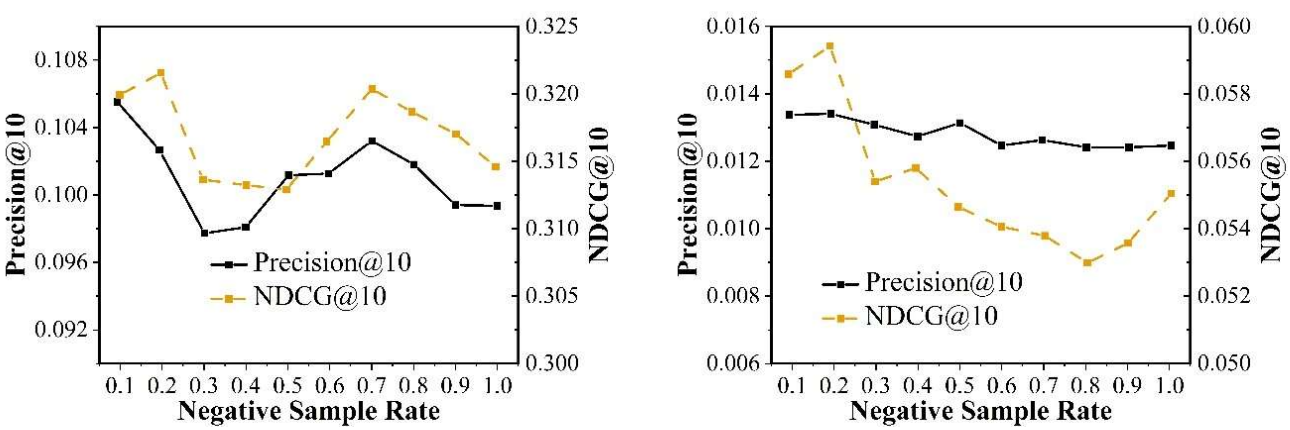
(d)Precision@10 (e)Recall@10 (f)NDCG@10

Figure 5: Algorithm performance comparison on dataset C



(a)Dataset A (b)Dataset B

Figure 6: Precision@10 growing trend during training



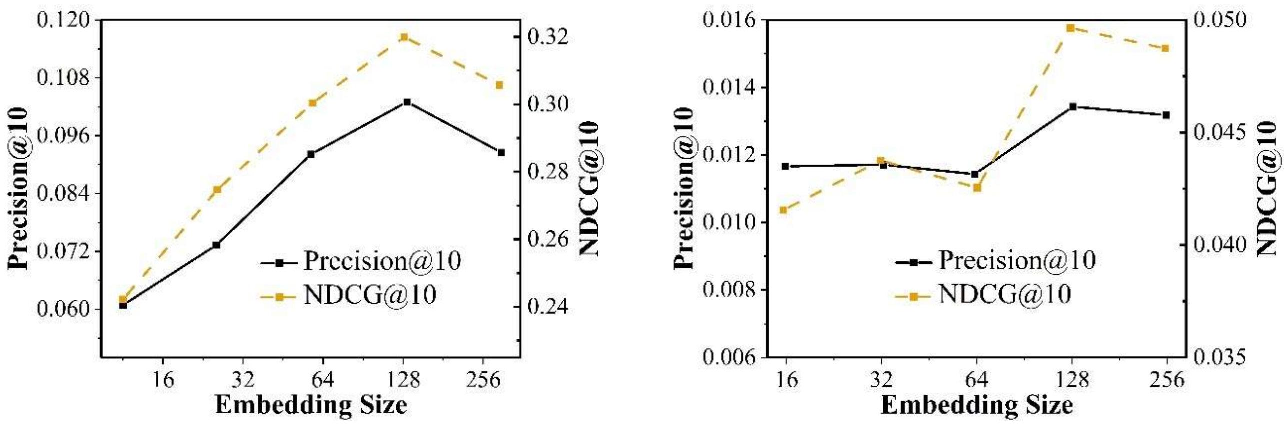
(a)Data set A (b)Data set B

Figure 7: The effect of negative sampling rate on data sets A and B

(2) Hyperparameter sensitivity analysis

The selection of hyperparameters has a key role in model training, so in order to verify the effects of three key hyperparameters negative sample sampling rate γ, embedding dimension d and number of hidden layers X of discriminative modeling on the model experimental results, this paper verifies the three hyperparameters by changing the values of hyperparameters for the recommended performance metrics of Precision@ on the A and B datasets. 10 and NDCG@10 results. The effect of negative sampling rate on datasets A and B is shown in Fig. 7, where (a)~(b) are datasets A and B. Under both datasets, GCNGAN can achieve the best performance when γ is between 0.1~0.2. The larger the γ, the sparser the interaction vectors, the more the model will focus too much on the negative samples and make the output close to zero instead of realizing the original goal of producing a true preference distribution, so this may degrade the model performance.

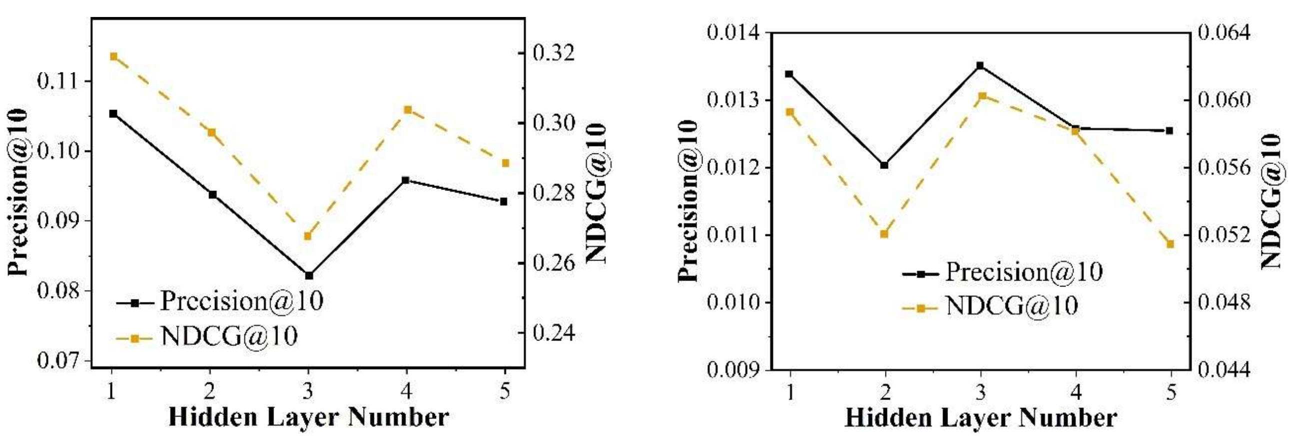
For different embedding dimensions containing different feature information, as shown in Fig. 8, the performance of GCNGAN increases with the increase of embedding dimension d, and reaches the best at embedding dimension d = 128. This indicates that GCNGAN can obtain better results by introducing more predictors to obtain stronger representation. However, if the size of the embedding dimension is too large (256), the parameters that need to be trained increase dramatically, which will affect the stability of the model training and lead to a decrease in recommendation accuracy.



(a)Data set A (b)Data set B

Figure 8: Influence of embedding dimension on A and B

Figure 9 illustrates the effect of the number of hidden layers X on the GCNGAN in datasets A and B. Typically, the best performance is obtained when $X=1$ and stacking more layers together does not necessarily improve the performance. The reason may be related to the training of the discriminative model. The more hidden layers are stacked, the more parameters the discriminative model needs to be trained, then the more difficult it is for the discriminative model to reach a steady state.



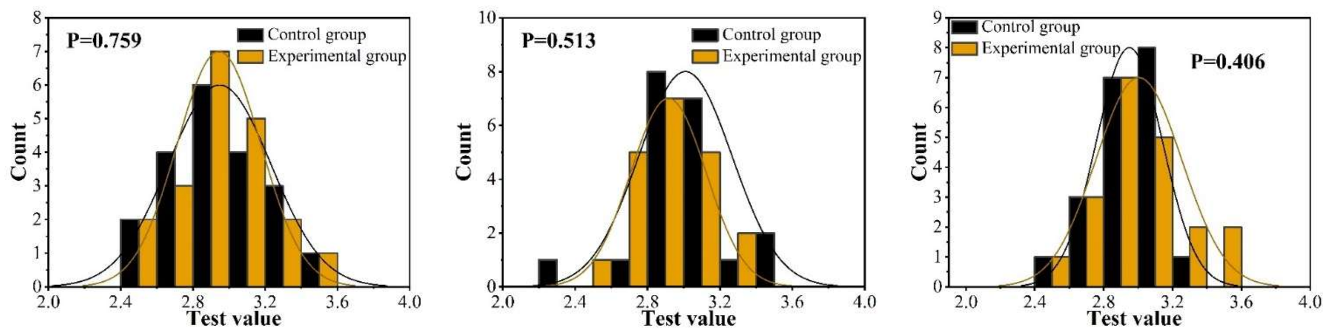
(a)Data set A (b)Data set B

Figure 9: Hide the effect of layers on A and B

V. B. Analysis of the effects of digital education applications of generative artificial intelligence

V. B. 1) Comparative analysis of students' digital literacy before the experiment

The study compared and analyzed the results of the students' digital literacy scale test between the experimental group and the control group before the experiment as a way of examining the level of students' digital theoretical knowledge, digital skills, and learning attitudes, and the results of the SPSS software analysis are shown in Fig. 10, where (a)~(c) are digital theoretical knowledge, digital skills, and learning attitudes, respectively. The results of the significance analysis show that there is no significant difference between the experimental and control groups in the research sample in terms of students' digital theory knowledge (P=0.759>0.05), digital skills (P=0.513>0.05), and learning attitudes (P=0.406>0.05). This result indicates that there is no significant difference between the experimental and control groups of students with comparable levels of digital theoretical knowledge, digital skills, and learning attitudes prior to the introduction of generative artificial intelligence techniques based on generative adversarial graph convolutional networks into digital education. Therefore, subsequent studies can determine the detailed impact and degree of effect of generative AI technology based on generative adversarial graph convolutional networks on students' digital literacy based on the pre- and post-test differences of students' digital literacy in each group.

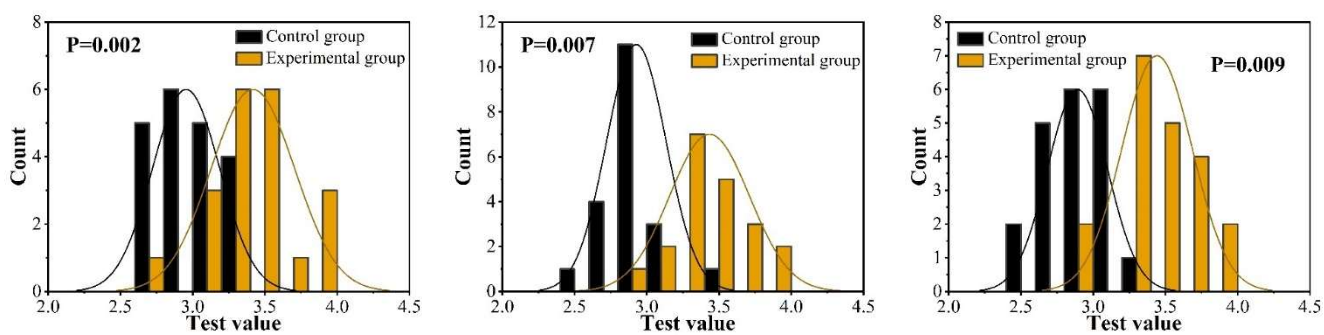


(a)Number theory knowledge (b)Digital Skills (c)Learning attitude

Figure 10: Comparative analysis of students' digital literacy before the experiment

V. B. 2) Comparative analysis of students' digital literacy after the experiment

In order to explore the impact of generative AI on students' digital educational literacy, the study compared and analyzed the data of students' digital literacy test after the experiment in the experimental group and the control group, and the results of the SPSS software analysis are shown in Figure 11. The data in the figure can be found that there is a significant difference in the level of digital theoretical knowledge (P=0.002<0.05), digital skills (P=0.007<0.05), and learning attitudes (P=0.009<0.05) about digital literacy between the experimental group and the control group students after the experiment. This result can indicate that the generative artificial intelligence technique based on generative adversarial graph convolutional network has a positive effect on the improvement of students' digital theoretical knowledge and digital skills, as well as can effectively improve the students with low digital literacy learning attitude.

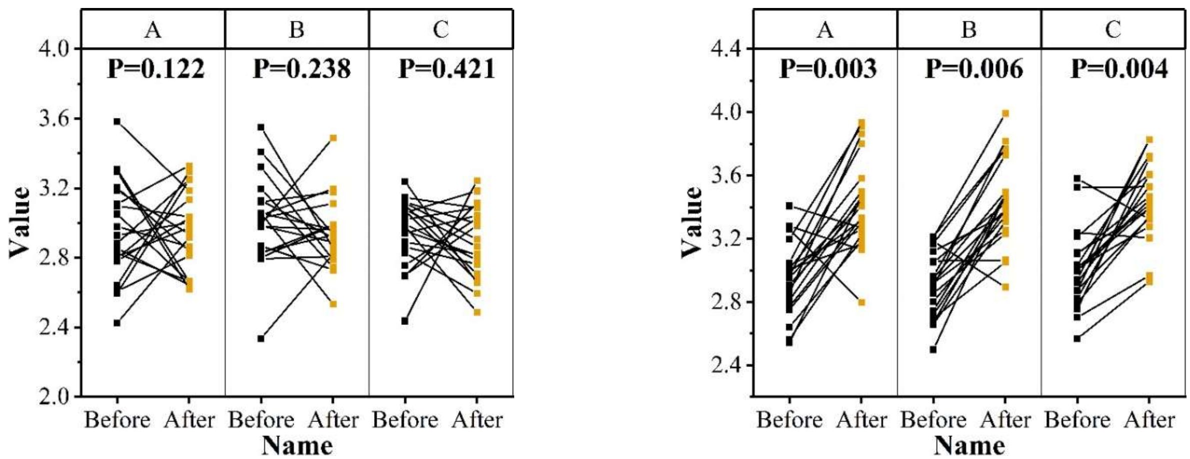


(a)Number theory knowledge (b)Digital Skills (c)Learning attitude

Figure 11: Comparative analysis of students' digital literacy after the experiment

V. B. 3) Comparative analysis of students' digital literacy before and after the experiment

In order to understand in detail the process and differences between generative AI technology and traditional digital education on students' digital literacy, the study combines the changes in students' digital literacy level during and before and after the experiment to conduct a comprehensive analysis. The results of the comparative analysis of students' digital literacy before and after the experiment based on SPSS are shown in Figure 12, where A, B, and C represent digital theoretical knowledge, digital skills, and learning attitudes, respectively, where (a)~(b) are the control group and the experimental group, respectively. According to the data performance in the figure, it can be seen that before and after the experiment of the students in the control group, there is no significant difference in digital theory knowledge (P=0.122>0.05), digital skills (P=0.238>0.05) and learning attitude (P=0.421>0.05). In the experimental group, it is obvious that there are significant differences in digital theoretical knowledge (P=0.003<0.05), digital skills (P=0.006<0.05) and learning attitudes (P=004<0.05), indicating that compared with the traditional teaching mode, the generative artificial intelligence technology designed in this paper has a more significant effect on the enhancement of students' digital literacy, which helps to promote the current digital education innovation and development.



(a)Control group (b)Experimental group

Figure 12: Comparison of students' digital literacy before and after the experiment

VI. Conclusion

In this paper, the generative artificial intelligence technology based on generative adversarial graph convolutional network is designed on the definition of generative artificial intelligence. In order to better integrate the technology into the process of digital education, it is proposed to use the technology in the form of embedded in the current digital education, in order to detect whether the technology can effectively promote the development of digital education, specially formulated a research program on the effect of the practical application of digital education integrating the generative AI technology, and with the help of the scale and SPSS software, the program was statistically analyzed. Through the data in the figure, it is found that there is no significant difference between traditional education methods in terms of digital theoretical knowledge, digital skills and learning attitudes (P>0.05), while the experimental group meets the condition of significance judgment (P<0.05), and the results of this data indicate that generative artificial intelligence technology based on generative antagonistic graphic convolutional network has a particularly obvious effect on the enhancement of the development of digital education.

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